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GENERALIZING MULTISTAIN IMMUNOHISTOCHEMISTRY TISSUE SEGMENTATION USING ONE-SHOT COLOR DECONVOLUTION DEEP NEURAL NETWORKS

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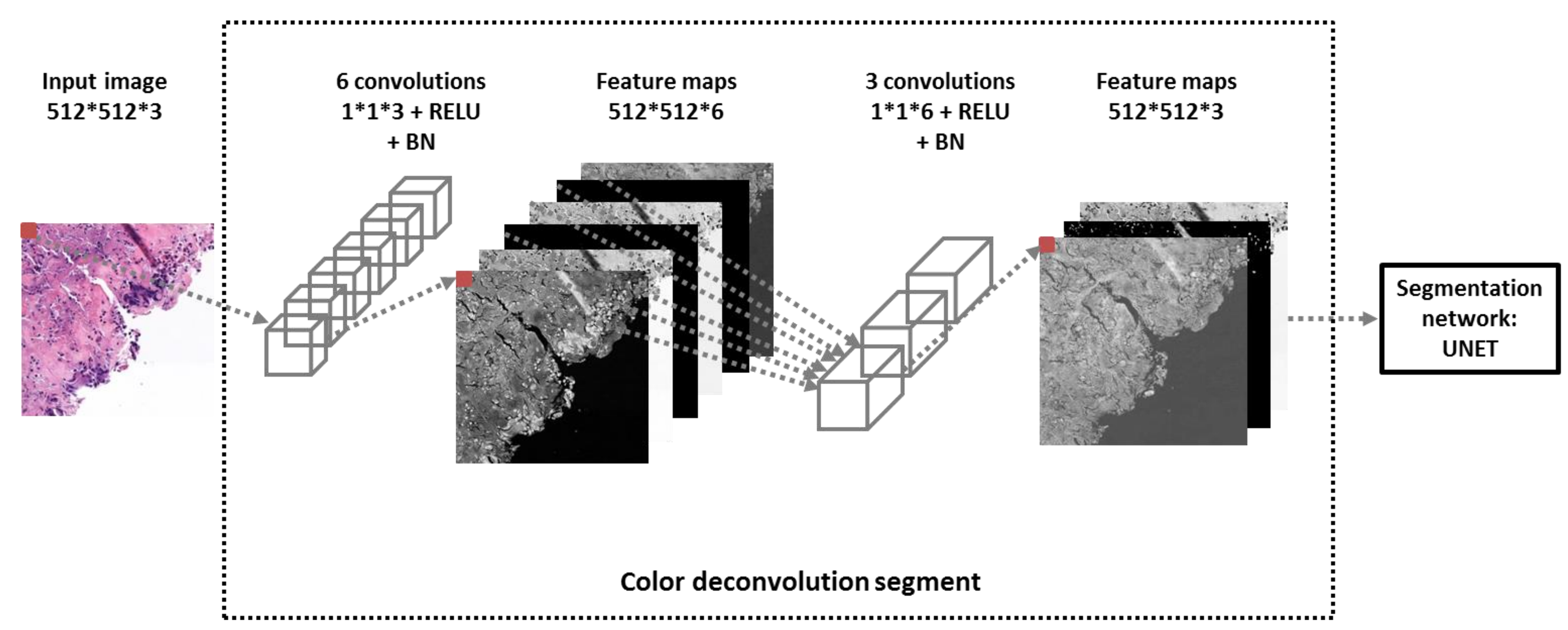
Abstract

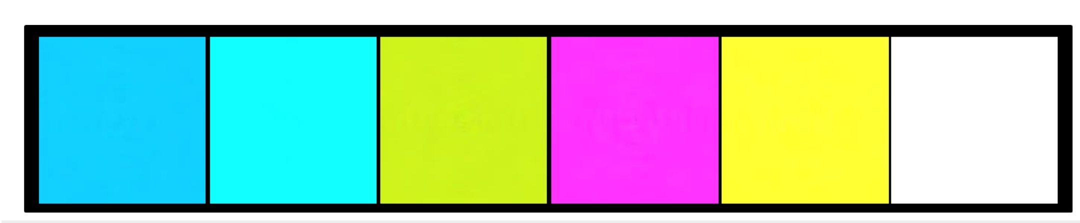
A key challenge in cancer immunotherapy biomarker research is quantification of pattern changes in microscopic whole slide images of tumor biopsies. Different cell types tend to migrate into various tissue compartments and form variable distribution patterns. Drug development requires correlative analysis of various biomarkers in and between the tissue compartments. To enable that, tissue slides are manually annotated by expert pathologists. Manual annotation of tissue slides is a labor intensive, tedious and error-prone task. Additionally, with the tools existing today it is also limited in precision and inconsistent between different experts and can even be inconsistent in different annotations by the same expert. Automation of this annotation process can improve accuracy and consistency while reducing workload and cost in a way that will positively influence drug development efforts. In this poster we present a novel one-shot color deconvolution deep learning method to automatically segment and annotate digitized slide images with multiple stainings into compartments of tumor, healthy tissue, and necrosis. We address the task in the context of drug development where multiple stains, tissue and tumor types exist and look into solutions for generalizations over these image populations.

Proposed architecture

Color deconvolution segment + UNET → CD-UNET



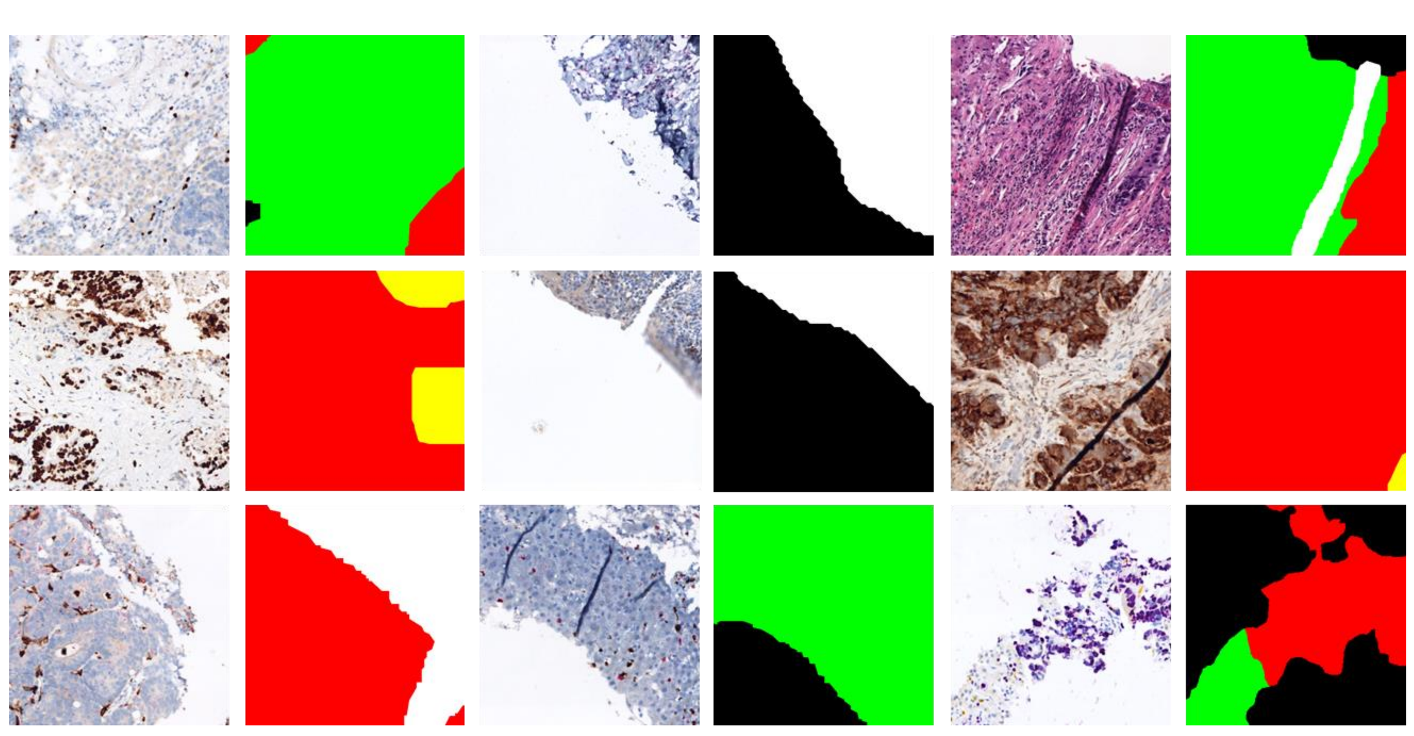
Activation maximization on the first layer's filters



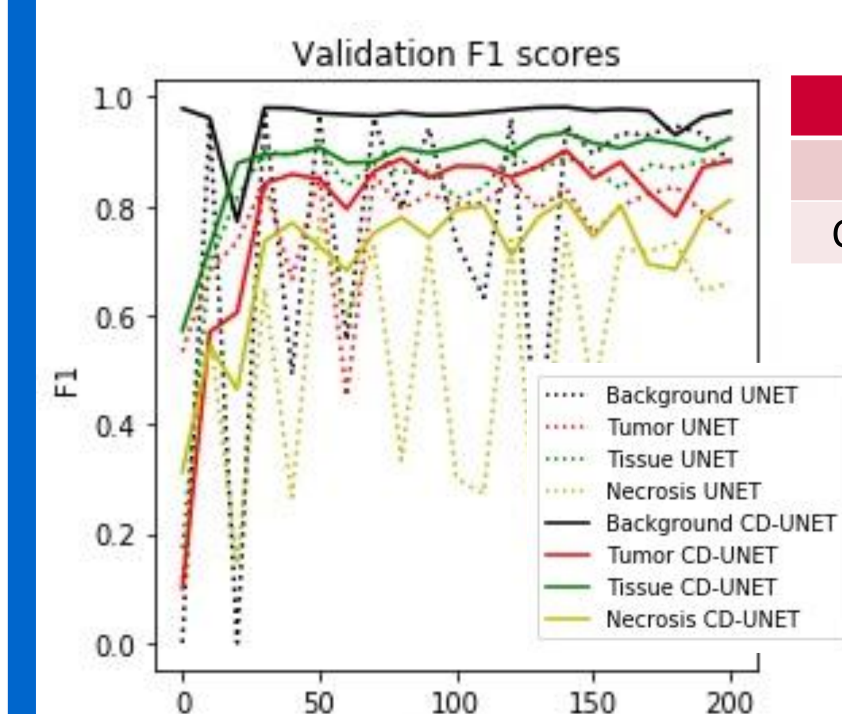
→ The resulted images correspond to different stain colors.

Data

- 77 wsi of Colorectal Carcinoma metastases in liver tissue from biopsy and surgical specimen slides annotated by an expert pathologist
- Stainings : H&E + 8 IHCs
- Magnification : 10x
- Training : 51 slides → 16834 patches (512*512)
- Segmentation classes: tumor, tissue, necrosis, background
- Data augmentation



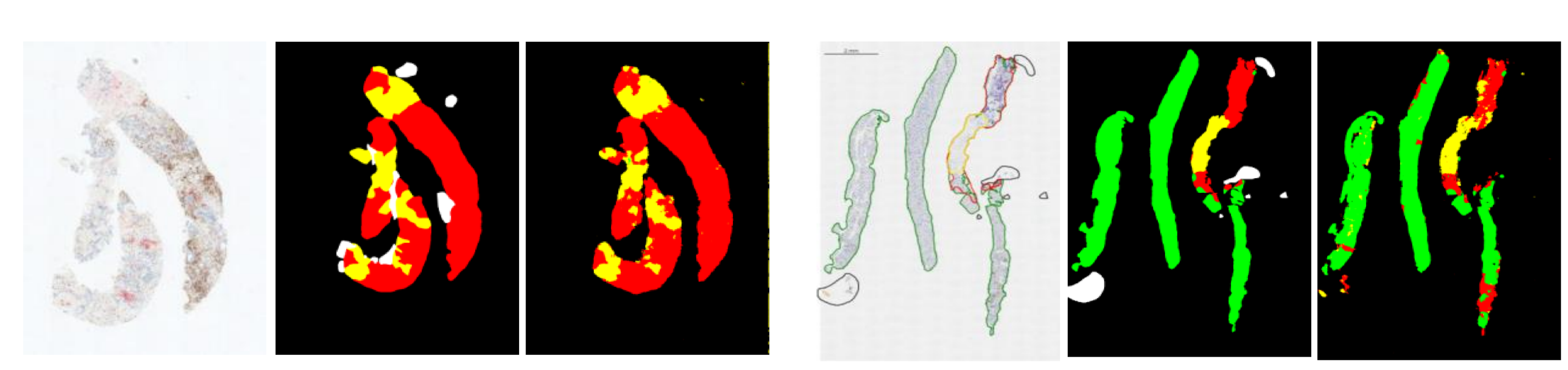
CD-UNET vs UNET



	Bg	Tumor	Tissue	Necrosis
UNET	0.92	0.52	0.89	0.60
CD-UNET	**0.99**	**0.88**	**0.90**	**0.80**

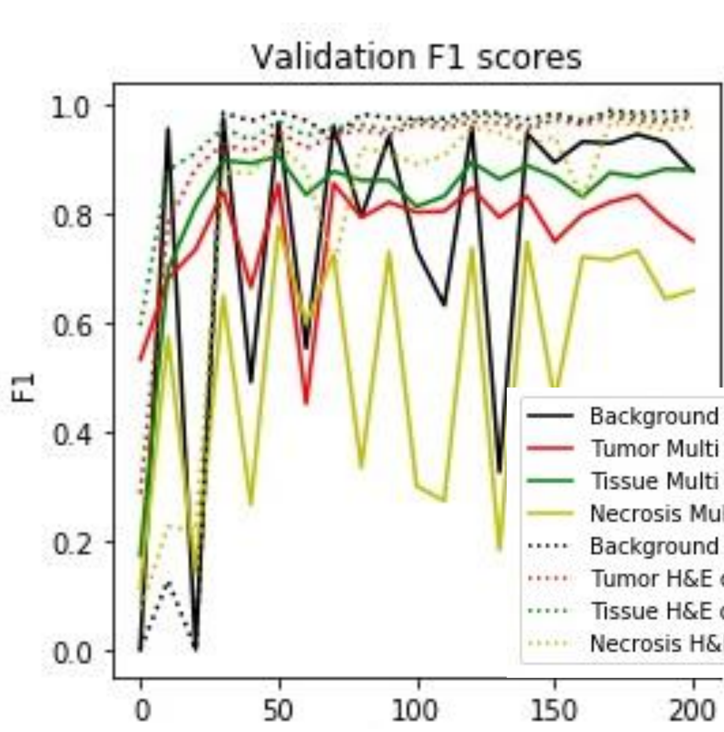
→ Color deconvolution segment improved convergence smoothness and speed and generalization capacity.

CD-UNET segmentation output examples



Original image GT CD-UNET Original image GT CD-UNET

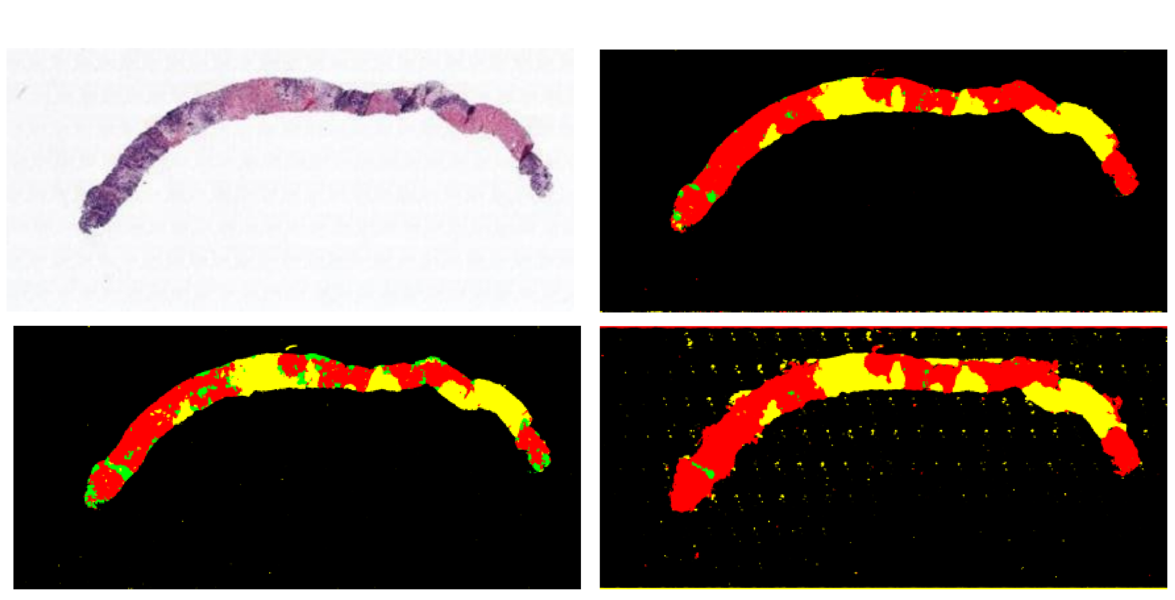
Single stain vs multiple stains training



	Bg	Tumor	Tissue	Necrosis
Multistain	0.63	0.20	**0.78**	0.44
H&E only	**0.99**	**0.85**	0.71	**0.88**

- The graph shows validation F1 scores of the different segmentation classes during 200 epochs of training.
- The table shows testing F1 scores.

→ Convergence is faster and testing results are better in the case of a single stain.

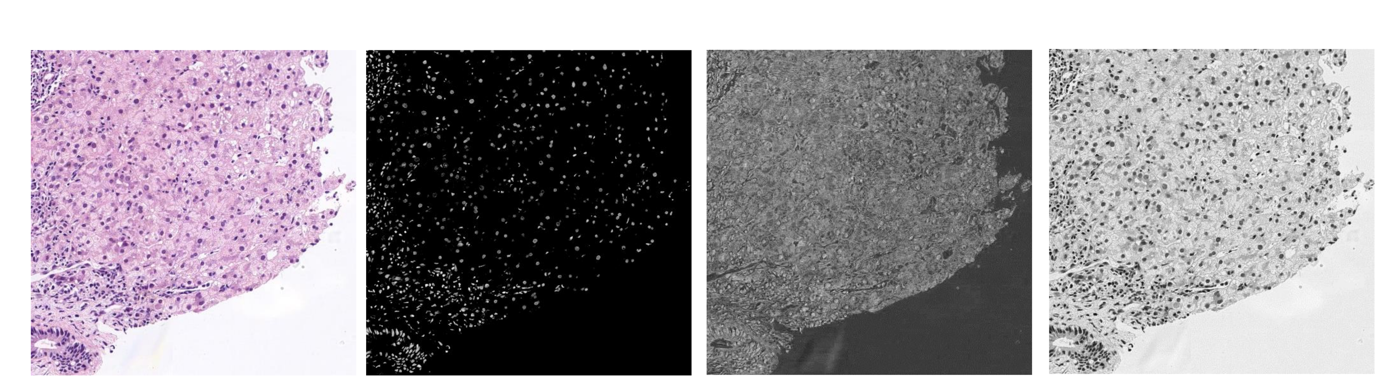


Original image GT

H&E only Multistain

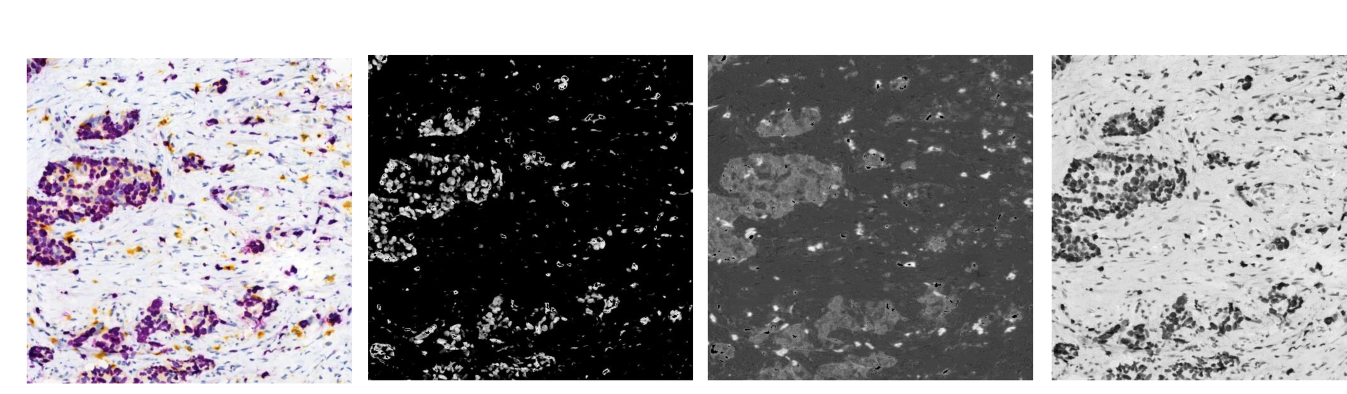
Color deconvolution outputs

H&E



Hematoxylin: blue cells Eosin : pink connective tissue Background

Ki67/CD8



CD8: purple cells Ki67: yellow cells Background

→ The visualization of the outputs of the color deconvolution segment using different stainings as inputs shows the added layers actually learned to separate between different stain channels for the different stain types.